

GLACE: The Global Land-Atmosphere Coupling Experiment.

2. Analysis

Zhichang Guo¹, Paul A. Dirmeyer¹, Randal D. Koster², Gordon Bonan³, Edmond Chan⁴, Peter Cox⁵, C.T. Gordon⁶, Shinjiro Kanae⁷, Eva Kowalczyk⁸, David Lawrence⁹, Ping Liu¹⁰, Cheng-Hsuan Lu¹¹, Sergey Malyshev¹², Bryant McAvaney¹³, J.L. McGregor⁶, Ken Mitchell¹¹, David Mocko¹⁰, Taikan Oki¹⁴, Keith W. Oleson³, Andrew Pitman¹⁵, Y.C. Sud², Christopher M. Taylor¹⁶, Diana Verseghy⁴, Ratko Vasic¹⁷, Yongkang Xue¹⁷, and Tomohito Yamada¹⁴

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¹ Center for Ocean-Land-Atmosphere Studies, Calverton, MD, 20705, USA

² NASA Goddard Space Flight Center, Greenbelt, MD, 20771, USA

³ National Center for Atmospheric Research, Boulder, CO 80307, USA

⁴ Meteorological Service of Canada, Toronto, Ontario M3H 5T4, Canada

⁵ Centre for Ecology & Hydrology (CEH) Dorset, Dorset DT2 8ZD, United Kingdom

⁶ Geophysical Fluid Dynamics Laboratory, Princeton, NJ 08542, USA

⁷ Research Institute for Humanity and Nature, Kyoto 602-0878, Japan

⁸ CSIRO Atmospheric Research, Aspendale, Victoria 3195, Australia

⁹ University of Reading, Reading, Berkshire RG66 BB, UK

- 1 ¹⁰ Science Applications International Corporation, Beltsville, MD 20705, USA
- 2 ¹¹ National Centers for Environmental Prediction, Camp Springs, MD 20746, USA
- 3 ¹² Princeton University, Princeton, NJ 08544, USA
- 4 ¹³ Bureau of Meteorology Research Centre, Melbourne, Victoria 3001, Australia
- 5 ¹⁴ University of Tokyo, Tokyo 153-8505, Japan
- 6 ¹⁵ Macquarie University, North Ryde, New South Wales 2109, Australia
- 7 ¹⁶ Centre for Ecology and Hydrology, Wallingford, Oxfordshire OX10 8BB, UK
- 8 ¹⁷ University of California, Los Angeles, CA 90095, USA

Abstract

The twelve weather and climate models participating in the Global Land-Atmosphere Coupling Experiment (GLACE) show both a wide variation in the strength of land-atmosphere coupling and some intriguing commonalities. In this paper, we address the causes of variations in coupling strength – both the geographic variations within a given model and the model-to-model differences. The ability of soil moisture to affect precipitation is examined in two stages, namely, the ability of the soil moisture to affect evaporation, and the ability of evaporation to affect precipitation. Most of the differences between the models and within a given model are found to be associated with the first stage – an evaporation rate that varies strongly and consistently with soil moisture tends to lead to a higher coupling strength. The first stage differences reflect identifiable differences in model parameterization and model climate. Intermodel differences in the evaporation-precipitation connection, however, also play a key role.

1. Introduction

Interaction between the land and atmosphere plays an important role in the evolution of weather and the generation of precipitation. Soil moisture may be the most important state variable in this regard. Much research has been conducted on the effects of soil wetness variability on weather and climate, encompassing various observational studies (e.g., Namais 1960; Betts et al. 1996; Findell and Eltahir 2003) and theoretical treatments (e.g., Entekhabi et al 1992, Eltahir 1998). These studies notwithstanding, the strength of land-atmosphere interaction is tremendously difficult to measure and evaluate. Consider, for example, attempts to quantify the impact of soil moisture on precipitation through joint observations of both. Precipitation may be larger when soil moisture is larger, but this may tell us nothing, for the other direction of causality – the wetting of the soil by precipitation – almost certainly dominates the observed correlation. Global-scale or even regional-scale estimates of land-atmosphere coupling strength simply do not exist.

This difficulty motivates the use of numerical climate models to address the land-atmosphere feedback question. With such models, idealized experiments can be crafted and sensitivities carefully examined. A few recent examples include the studies of Dirmeyer (2001), Koster and Suarez (2001), Schlosser and Milly (2002), and Douville (2003).

Modeling studies, of course, are far from perfect. The ability of land states to affect atmospheric states in atmospheric general circulation models (AGCMs) is not explicitly prescribed or parameterized, but is rather a net result of complex interactions between numerous process parameterizations in the model. As a result, land-atmosphere interaction varies from model to model, and this model dependence affects AGCM-based interpretations of land use

1 impacts on climate, soil moisture impacts on precipitation predictability, and so forth (Koster et
2 al. 2002). The broad usage of GCMs for such research and the need for an appropriate
3 interpretation of model results makes necessary a comprehensive evaluation of land-atmosphere
4 interaction across a broad range of models. The Global Land-Atmosphere Coupling Experiment
5 (GLACE) was designed with this in mind.

6 In GLACE, twelve AGCMs perform the same highly-controlled numerical experiment,
7 an experiment designed to characterize land-atmosphere interaction quantitatively. In GLACE,
8 three 16-member ensembles of 3-month simulations are performed: an ensemble in which the
9 land states of the different members vary independently and interact with the atmosphere (W); an
10 ensemble in which the same geographically- and temporally-varying land states are prescribed
11 for each member (R), and an ensemble in which only the subsurface soil moisture values are
12 prescribed for each member (S). By quantifying the inter-ensemble similarity of precipitation
13 time series within each ensemble and then comparing this similarity between ensembles, we can
14 isolate the impact of the land surface on precipitation – we can quantify the degree to which the
15 atmosphere responds consistently to anomalies in land states. (The degree of consistent response
16 is hereafter referred to as the “land-atmosphere coupling strength”). The companion paper
17 (Koster et al., this issue) describes the experiment and analysis approach in detail and provides
18 an overview of the model comparison.

19 Note that the focus on subsurface moisture (ensemble S above) is of special interest. It is
20 well accepted that the variability of soil moisture is much slower than that of atmospheric states
21 (Dirmeyer 1995). Hope for improving the accuracy of seasonal forecasts lies partly with the
22 “memory” provided by soil moisture. By quantifying the impact of subsurface soil moisture on

1 precipitation, GLACE helps evaluate a model's ability to make use of this memory in seasonal
2 forecasts.

3 Koster et al. (this issue) and Koster et al. (2004) highlight "hot spots" of land-atmosphere
4 coupling -- regions of strong coupling between soil moisture and precipitation that are common
5 to many of the AGCMs. What causes such commonalities, and how do they relate to
6 climatological and hydrological regime? Which aspects of land surface and atmospheric
7 parameterization cause the large model-to-model differences of coupling strength among the
8 AGCMs? How are the signals that exist in the land surface states transmitted to and manifested
9 in the atmosphere states?

10 Such critical questions lie at the heart of our understanding of land-atmosphere feedback.
11 Arguably, a fully comprehensive analysis of these questions would require additional sensitivity
12 experiments and model-dependent analysis techniques, all of which are beyond the scope of
13 GLACE. Nevertheless, the design of GLACE and the diagnostics provided by the participants
14 do provide powerful insight into how a soil moisture signal is translated into an evaporation
15 signal, which in turn is translated to a precipitation signal – and for how and why these
16 translations differ amongst the AGCMs. Such an analysis is presented in the present paper. First,
17 section 2 addresses the geographical patterns of coupling strength seen in the models. Section 3
18 then provides an analysis of intermodel differences in coupling strength. Further discussion and a
19 summary of our findings are presented in section 4.

20 **2. Commonalities in coupling strength**

1 The multi-model synthesis used in the companion paper (Koster et al., this issue) proves
2 effective for identifying robust regions (across models) of significant soil moisture impact on
3 precipitation and near-surface air temperature – the identified regions are less subject to
4 problems in the process parameterizations of any individual model. We can apply the same
5 multi-model analysis procedure here to the other model variables. As in the companion paper
6 (see section 5 of Part 1), we first disaggregate variables from each model to the same fine grid,
7 one with a resolution of $0.5^\circ \cdot 0.5^\circ$. We then average the results on that grid across the models,
8 applying the same weight to each model.

9 As explained in section 4 of the companion paper (see eq. 2), the variable Ω_v measures
10 the degree to which the sixteen time series for the variable v generated by the different ensemble
11 members are similar. Thus, $\Omega_v(S) - \Omega_v(W)$ or $\Omega_v(R) - \Omega_v(W)$ are measures of the regulation of
12 land states on the atmospheric variable v . As in the companion paper, we computed Ω_v and the
13 standard deviation σ_v for each model across 224 aggregated 6-day totals (16 ensemble members
14 times 14 intervals in each simulation time-series).

15 The upper left panel of Fig. 1 shows the mean of $\Omega_P(S) - \Omega_P(W)$ for precipitation across
16 the 12 models, i.e., the model-average impact of subsurface soil moisture on precipitation. This
17 figure essentially repeats the contents of the top panel of Figure 9 from the companion paper.
18 Notice that the larger soil moisture impacts on precipitation generally occur in the transition
19 zones between humid and arid climates, such as the central Great Plains of North America, the
20 Sahel in Africa, and the northern and western margins of the Asian monsoon regions.

How can we characterize the evaporation signal that best serves as a link between soil moisture anomalies and precipitation – that best explains the geographical variations of $\Omega_P(S) - \Omega_P(W)$ shown in Figure 1a, if a local soil moisture influence is assumed? In Figure 2, we argue that such an evaporation signal (as a proxy for the full surface energy balance) must have two characteristics: it must respond similarly to soil moisture variations, and it must show wide temporal variations. The four panels show idealized evaporation time-series (i.e., not from real simulations) for 16 parallel ensemble members under four situations: (i) a low similarity in the evaporation time series [i.e., a low value of $\Omega_E(S) - \Omega_E(W)$] and a low variability of evaporation [i.e., a low value of $\sigma_E(W)$], (ii) a low similarity but a high variability of evaporation, (iii) a high similarity yet a low variability of evaporation, and (iv) a high similarity and a high variability of evaporation. Clearly, cases (i) and (ii) cannot lead to a “robust” precipitation response (i.e., a similar response across ensemble members) to soil moisture, given that evaporation is the key link between the two, and evaporation itself has no robust response to soil moisture. A robust evaporation response, however, does not by itself guarantee a robust precipitation response. For case (iii), the evaporation response to soil moisture is robust, but the atmosphere would not see a strong signal at the surface due to the low evaporation variability. Only the fourth situation provides a signal for the atmosphere that is both robust and strong.

We argue that for soil moisture to affect evaporation, both $\Omega_E(S) - \Omega_E(W)$ and $\sigma_E(W)$ must be suitably high. In other words, the product $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$ must be high. We use this diagnostic product throughout this paper to characterize the ability of a local evaporation signal to support land-atmosphere feedback. (We assume here that $\sigma_E(W)$ and $\sigma_E(S)$ are similar; analysis of the model data confirms this.) The product proves effective for our purposes, despite

1 being a potentially suboptimal diagnostic – it may, for example, already contain some implicit
 2 feedback information through the potential co-evolution of σ_E and σ_P , and thus it may partly
 3 reflect the character of the atmosphere and its role in feedback. Still, the other direction of
 4 causality (precipitation variability causing evaporation variability) is undoubtedly dominant, and
 5 regardless of the source of the evaporation variability, the product still serves as a
 6 characterization of the evaporation signal itself.

7 The upper right panel of Fig. 1 shows the global distribution of $\Omega_E(S) - \Omega_E(W)$ (again,
 8 averaged across the models), and the lower left panel shows that for $\sigma_E(W)$. Neither diagnostic
 9 by itself explains all characteristics of the distribution of $\Omega_P(S) - \Omega_P(W)$ (top left panel) . The
 10 lower right panel shows the distribution of the product $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$ averaged over
 11 the 12 models (note the different scales among panels). The spatial correlation between the
 12 geographical patterns of $\Omega_P(S) - \Omega_P(W)$ and the product is 0.46, which is larger than that
 13 between $\Omega_P(S) - \Omega_P(W)$ and either factor alone (0.35 and 0.2 for $\sigma_E(W)$ and $\Omega_E(S) - \Omega_E(W)$,
 14 respectively). Of course, none of these spatial correlations is particularly large. Nevertheless, as
 15 will be shown in section 3, the diagnostic product $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$ explains well the
 16 intermodel differences in coupling strength at a given location, much better than can either factor
 17 alone.

18 The scatter plots in Figure 3 illustrate further the control of hydrological regime on the
 19 product $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$. The lines represent a best fit through the mean of the
 20 dependent variable in bins of 200 points each. A roughly linear inverse relationship is seen
 21 between the soil wetness and $\Omega_E(S) - \Omega_E(W)$. The scatter plot shows that ET (the total

1 evaporation) is more sensitive to land state in dry climates than in areas with moderate soil
 2 wetness. The results are consistent with the findings of Dirmeyer et al. (2000), who showed that
 3 the sensitivity of surface fluxes to variations in soil moisture generally concentrates at the dry
 4 end of the range of soil moisture index. In contrast, the standard deviation of ET (σ_E) is not large
 5 for low soil moisture, simply because ET itself is small in such regions. Put together, the product
 6 $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$ has minima for very wet and very dry soils, and it is largest for
 7 intermediate soil moisture values (degree of saturation between 0.1 and 0.4; see Figure 3c).
 8 Figure 3d shows, for comparison, how $\Omega_P(S) - \Omega_P(W)$ varies with soil moisture; the relationship
 9 shows a hint of that seen for $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$, particularly at the extremes.

10 The conclusions above were obtained from a multi-model average. We now examine,
 11 with some simple statistical indicators, their relevance to individual models. First, consider the
 12 panels on the left in Fig. 4. The top panels show the inter-model standard deviation of
 13 $\Omega(S) - \Omega(W)$ among the 12 models, and the bottom panels show the ratio of the mean to the
 14 standard deviation. The pattern of the inter-model standard deviation of $\Omega_E(S) - \Omega_E(W)$ (left)
 15 largely resembles the field of $\Omega_E(S) - \Omega_E(W)$ itself (Fig. 1), except for enhanced variability over
 16 arid regions. The ratio serves as a measure of signal to noise, showing where there is the least
 17 uncertainty among models. The pattern of the ratio resembles that of the mean in the upper right
 18 panel in Fig. 1, with some shift away from the arid regions, giving a distribution that overlaps
 19 many of the world's major agricultural areas.

20 The implication of the left panels in Fig. 4 is that the regions of strong ET similarity are
 21 relatively common among the models. The same cannot be said about precipitation similarity
 22 $(\Omega_P(S) - \Omega_P(W))$. The right panels in Fig. 4 show the standard deviation and signal-to-noise ratio

for precipitation similarity. The ratio of the mean to the standard deviation for precipitation similarity is much weaker than for ET and more dominated by noise. Only over a few regions (e.g., northern India, China, Pakistan, and parts of sub-Saharan Africa) are there sizeable areas that approach a ratio of unity (note the difference in scale). Note also that the strongest signal-to-noise values are still located in regions with strong levels of 12-model mean precipitation similarity in the upper left panel of Fig. 1. Large, inter-model variability, however, predominates over most of the globe.

3. Comparison among GCMs

While the models show some similarities in the geographical pattern of land-atmosphere coupling strength, they also show some wide disparities. Global maps of $\Omega_P(S) - \Omega_P(W)$ were provided in Fig. 5 of Part 1 for all twelve GCMs. The major features found in the multi-model mean are seen in many of the models. Some areas, though, such as the Northern Amazon and Orinoco Basins, show significant differences. Also, the coupling strength in general seems relatively large in the GFDL, NSIPP, and CAM3 models, whereas that for GFS/OSU it seems very weak.

Similar commonalities and disparities among AGCMs can be found in the impacts of soil moisture on ET. We showed in section 2 that the diagnostic $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$, which measures the degree to which the evaporation signal is both similar and strong, appears to explain much of the geographical variation in precipitation similarity for the mean of the models. Figure 5 shows global maps of this product for each model. The models tend to agree in the placement of larger values in the transition regions between humid and dry climates, but disparities abound. The GFDL model has the highest mean values for the product, whereas

1 GFS/OSU has by far the lowest. Indeed, the low values for GFS/OSU by themselves can explain
2 this model's globally low precipitation similarity values.

3 Differences in this diagnostic product are indeed related to differences in land-
4 atmosphere coupling strength. Figure 6 shows how $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$ varies with
5 $\Omega_P(S) - \Omega_P(W)$ for the average of global ice-free land points and for the three “hot spot” regions
6 delineated by dashed lines in Fig. 1. The high r^2 values for the hot spot regions (0.86, 0.84 and
7 0.51 over the Sahel, northern India, and the central Great Plains of North America, respectively)
8 suggest that the intermodel differences in $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$ are strongly related – and,
9 given the arguments in section 2, largely explain – the intermodel differences in $\Omega_P(S) - \Omega_P(W)$ in
10 these regions. (Note that for the global mean in Fig. 6a, the r^2 value appears to be determined
11 mostly by the position of one point.) Supplemental calculations show that $\Omega_E(S) - \Omega_E(W)$ alone
12 would produce r^2 values of 0.84, 0.56, and 0.38, respectively, in the hot spot regions, while
13 $\sigma_E(W)$ alone would produce r^2 values of 0.11, 0.62, and 0.40, respectively.

14 Of course, the relationship is not perfect, due to sampling error, the inability of the
15 diagnostic to capture fully the evaporation signal's impact on land-atmosphere feedback, and the
16 fact that the models also differ in the coupling mechanism between ET and precipitation (section
17 3c). Indeed, the separation of the pathway linking soil moisture anomalies and precipitation
18 generation into two parts – the segment between soil moisture anomalies and evaporation
19 anomalies and that between evaporation anomalies and precipitation generation – is useful for
20 understanding the intermodel differences in $\Omega_P(S) - \Omega_P(W)$. In essence, Figure 6 suggests that

1 while the first segment is the most important for explaining these differences (the r^2 values for
2 between the associated diagnostic and $\Omega_P(S)$ - $\Omega_P(W)$ are high), it is not all-important.

3 In the remainder of this section, we focus more closely on the models' representations of
4 these two segments. We construct a series of indices to measure the overall strength of each
5 segment within each model, as well as the strength of coupling for the entire path from soil
6 wetness to precipitation. The results are summarized in Table 1.

7
8 *a. Soil-precipitation coupling: Net effect*

9 The first column after the list of models in Table 1 shows the global mean of the
10 precipitation similarity diagnostic $\Omega_P(S)$ - $\Omega_P(W)$ calculated over all non-ice land points. The
11 next column provides the rank of the model (1 indicating the highest global mean, and thus the
12 model with the strongest control of sub-surface soil moisture on precipitation). Some grouping
13 is evident; three models (GFDL, NSIPP and CAM3) show similarly large values of the global
14 mean index (between 0.032 and 0.040), and another group (CSIRO, UCLA, CCSR, COLA,
15 GEOS, and BMRC) shows much lower values, ranging from 0.005-0.014. The HadAM3 and
16 GFS/OSU models show almost no impact of sub-surface soil wetness on precipitation.

17 A comparison of the R and S experiments reveals how the specification of “faster” land
18 variables (temperatures, etc.) affects the model rankings. In Fig. 7, global means of $\Omega_P(S)$ - $\Omega_P(W)$
19 are plotted against $\Omega_P(R)$ - $\Omega_P(W)$ for each model. Similar groupings are evident. Notice that the
20 rankings are similar (i.e., the points cluster along a diagonal line with positive slope) despite the
21 differences in the scales of the axes. In general, if specifying subsurface soil moisture has a

relatively large impact on the similarity of rainfall in a model, then the specification of all land variables in the model will also have a relatively large impact on precipitation.

b. Segment 1: Soil-ET coupling

The first segment of the path in soil-precipitation coupling is from soil wetness variations to ET variations, which we characterize with the diagnostic $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$. Columns 4 and 5 in Table 1 show respectively the global mean of this diagnostic for each model (calculated over all non-ice land points) and the model's corresponding rank. The GFDL model clearly has the strongest link between subsurface soil wetness and ET. There is a significant gap to the model in second place (CCCma) and then a fairly continuous spectrum down to the 11th model (COLA). GFS/OSU has a very weak coupling between soil wetness and ET and is a clear outlier. Note that the centers of the topmost soil layers of the GFDL, BMRC, CCCma and HadAM3 models are at or are deeper than 5 cm, meaning that for each of these four models, the soil moisture was continually specified in the topmost layer in the S experiment. Thus, for these four models only, bare soil evaporation was directly affected by the soil moisture specification in case S, helping to increase $\Omega_E(S) - \Omega_E(W)$. (In the GFS/OSU model, the topmost soil layer was not continually specified in the S ensemble even though the center is exactly 5 cm from the surface. Although this implementation of the experiment is not precisely correct, it should have a limited impact on the computed global average of the $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$ field. The whole of the root zone encompasses a much larger soil volume than the surface layer, and

1 supplemental analysis of GFS/OSU's evaporation fields shows that although bare soil
2 evaporation is dominant in some regions, transpiration dominates on the global scale.)

3 As discussed in section 2, the diagnostic $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$ captures two separate
4 aspects of the evaporation signal: its variability and its similarity. Figure 8 shows, for each of
5 the regions analyzed in Figure 6, the individual quantities σ_E and $\Omega_E(S) - \Omega_E(W)$ for each model.
6 This breakdown helps us relate differences in the soil-ET coupling to differences in climate
7 regime and model parameterization. Differences in σ_E relate mostly to differences in the
8 models' background climatologies (though σ_E may potentially be amplified through its
9 coevolution with σ_P during feedback). Differences in $\Omega_E(S) - \Omega_E(W)$, on the other hand, relate
10 mostly to differences in incident radiative energy and in the details of the land surface
11 parameterization – particularly, in those details defining the sensitivity of evaporation to soil
12 moisture variations. For example, notice that in panels a) through c) BMRC tends to have
13 moderately high similarity in its evaporation fluxes $(\Omega_E(S) - \Omega_E(W))$ but very low variability (σ_E)
14 – the type of behavior idealized in the third panel of Figure 2. The low σ_E for BMRC reflects
15 the relatively low mean and variability of the precipitation forcing (not shown) for that model
16 over most of the areas examined – i.e., it results from the model's background climatology. The
17 same arguments regarding evaporation variability apply, to a degree, to the CCSR/NIES model,
18 particularly over northern India and the Sahel. The GFDL model, on the other hand, shows
19 relatively high precipitation variability on a global scale, helping to promote evaporation
20 variability. Coupled with the moderate-to-high $\Omega_E(S) - \Omega_E(W)$ values for this model, the

1 diagnostic $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$ is especially high, promoting strong land-atmosphere
2 feedback.

3 Now consider the COLA model. Evaporation (and precipitation) variability in the areas
4 studied is not particularly small for this model, but the evaporation similarity values are (case ii
5 in Fig 2). These low similarity values probably reflect this model's relatively high inter-
6 ensemble variability of net radiation (not shown).

7 Again, details of the land model parameterization – particularly those associated with
8 soil-water limited transpiration and how it relates in magnitude to bare soil evaporation and
9 canopy interception loss – probably explain most of the intermodel differences in $\Omega_E(S) - \Omega_E(W)$.
10 The parameterization in the GFS/OSU model, for example, must be responsible for this model's
11 very low $\Omega_E(S) - \Omega_E(W)$. In the India region, at least, the GFS/OSU model does produce a bare
12 soil evaporation that exceeds transpiration (not shown). (Curiously, another land model used at
13 NCEP– the NOAH LSM – shows substantial evaporation sensitivity to soil moisture variations
14 when coupled to NCEP's Eta regional model [Berbery et al., 2003].) A proper analysis of such
15 model parameterization differences would necessarily be complex and will not be addressed in
16 this paper.

17 Other climatic factors may also lead to intermodel differences in $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$.
18 For example, because this diagnostic peaks at intermediate values of soil wetness (Figures 3), the
19 model whose climatology produces the highest fractional area with such soil wetness values
20 might produce the highest average value for the diagnostic. Also, if a model shows large
21 similarity in evaporation rates in the free-running W experiment ($\Omega_E(W)$) due to the initialization

1 procedure or to the effects of the oceanic boundary conditions and seasonal radiation forcing
2 applied, the difference $\Omega_E(S) - \Omega_E(W)$ may have a small upper potential limit. Careful analysis of
3 the model output, however, shows that neither factor has a first-order impact on the ranking of
4 the models.

5 Finally, a comparison of the evaporation diagnostics computed from the R and S
6 experiments provides some interesting insights into the control of evaporation in the different
7 models. Figure 9a shows the global mean (over non-ice land points) of $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$
8 versus the corresponding global mean of $(\Omega_E(R) - \Omega_E(W)) \cdot \sigma_E(W)$. Because more variables (i.e.,
9 the fast variables, including surface soil moisture, skin temperature and canopy interception) are
10 specified in the R experiment than in the S experiment, we expect the evaporation similarity to
11 be larger for the R experiment, and thus we expect $(\Omega_E(R) - \Omega_E(W)) \cdot \sigma_E(W)$ to be larger than
12 $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$. This is seen in general on the global scale. Some models (CAM3,
13 GFS/OSU, and COLA) show a relatively large difference between $(\Omega_E(R) - \Omega_E(W)) \cdot \sigma_E(W)$ and
14 $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$, suggesting that evaporation in these models is more strongly controlled
15 by the fast variables. The higher values of the diagnostic for the R experiment have consequent
16 impacts on the land-atmosphere coupling strength in that experiment, $\Omega_P(R) - \Omega_P(W)$ (Figure 7).

17 Similar behavior is observed over the Great Plains and the Sahel (Figure 9bd).
18 Interestingly, the specification of the fast variables over India (Figure 9c) has an impact on only
19 a handful of models (COLA, UCLA, GFS/OSU, CAM3, and CCCma) – the rest of the models
20 fall close to the 1:1 line.

1

2 *c. Segment 2: ET-precipitation coupling*

3 The land surface model and the background climatology may combine to produce a
4 strong and similar evaporation signal, as in the lowest panel of Figure 2. For this to be translated
5 into an impact on precipitation, however, the second segment of land-atmosphere feedback – the
6 link between evaporation and precipitation – must be strong. Returning to Table 1, we present
7 two different indices to measure this link. Both indices are inferred from joint analysis of
8 diagnosed precipitation and ET similarities.

9 The first index is simply the spatial pattern correlation between $(\Omega_E(R) - \Omega_E(W)) \cdot \sigma_E(W)$
10 and $\Omega_P(R) - \Omega_P(W)$ across the globe. The idea is simple: if the control of ET on precipitation is
11 local and strong, then the spatial patterns of the evaporation diagnostic and the precipitation
12 similarity should be highly correlated. The correlations from the R experiment are similar to
13 those from the S experiment; we use those from the R experiment here simply because they will
14 not be spuriously high due to the response of bare soil evaporation or interception loss to incident
15 precipitation.

16 The second index is the ratio between the global means (over non-ice land points) of
17 $\Omega_P(S) - \Omega_P(W)$ and $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$. This gives a global measure of how the second
18 segment of land-atmosphere coupling (i.e., between evaporation and precipitation) degrades the
19 link between soil moisture and precipitation, without regard for the “localness” or “remoteness”
20 of the evaporation impacts.

21 Table 1 shows that the two indices produce similar rankings among the models. The
22 CAM3 and NSIPP models rank considerably higher than the other models in both indices,

1 suggesting that their parameterizations for moist convection, boundary layer physics, and/or
 2 other atmospheric processes are especially sensitive to evaporation variations at the land surface.
 3 GEOS and HadAM3 show much lower rankings for the ET—P index than for the SW—ET
 4 index, suggesting that the ET-P connection is weak enough to lose whatever signal is transmitted
 5 from soil wetness to ET. Both CAM3 and COLA show strong values of the ET—P indices but
 6 do not rank high in the SW—ET index, suggesting that these models might have an even
 7 stronger coupling between soil wetness and precipitation if a different land surface
 8 parameterization were used or (in the case of the COLA model) if the net radiation were less
 9 variable. Finally, the small values of all indices for GFS/OSU and BMRC suggest that the lack
 10 of signal in ET may prevent any measure of ET—P coupling; again, a change of land surface
 11 scheme might alter dramatically the behavior of these two models.

12 The ratio-based index $(ET-P)_2$ can be used to interpret the scatter in Fig. 6a, the plot
 13 showing the relationship between globally-averaged numerator $\Omega_P(S) - \Omega_P(W)$ and denominator
 14 $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$ for the different models. The CAM3 and NSIPP models lie well above
 15 a fitted line through the points. The interpretation of the ratio-based index $(ET-P)_2$ explains
 16 why: these two models have atmospheres that are (relatively) sensitive to evaporation variations.
 17 Similarly, the fact that GEOS and HadAM3 lie below the fitted line can be explained by the
 18 relative insensitivity of their atmospheres to evaporation variations.

19 Figure 10 summarizes the results of separating land-atmosphere feedback into the two
 20 segments. The x-axis represents the first segment of the coupling, the link between soil wetness
 21 and ET. The y-axis represents the second segment, the link between ET and precipitation as
 22 provided by the correlation-based diagnostic $(ET-P)_1$. The number near each model name in

1 Figure 10 shows how the model ranks in total coupling strength over all ice-free land points
2 (from column 3 of Table 1).

3 The coupling strength in a model, of course, is controlled by the nature of both segments
4 of the coupling. The closer a model is to the upper right corner of the plot, the more likely a soil
5 wetness anomaly can propagate through the ascending branch of the hydrologic cycle and affect
6 precipitation. The figure immediately highlights some of the results outlined above; for example,
7 the low coupling strengths of the BMRC and COLA models results from their weak soil
8 moisture - evaporation connection, whereas the high coupling strength for the GFDL model
9 results from its very strong soil moisture - evaporation connection. Coupling strength is strong
10 in models such as NSIPP and CAM3 mostly because of the strong connection between ET and
11 precipitation in these two models. The HadAM3, on the other hand, shows the weakest coupling
12 between ET and precipitation, and it thus has one of the weakest coupling strengths. The
13 HadAM3 result is consistent with findings from a recent study (Lawrence and Slingo 2004) that
14 showed how the inclusion of predicted vegetation phenology in this model had no impact on
15 precipitation, even though soil wetness, surface latent heat flux, and near surface air temperature
16 were all significantly affected over large areas of the globe. The GFS/OSU model lies near the
17 origin and has the weakest coupling strength because both soil moisture - evaporation connection
18 and coupling between ET and precipitation are weak.

19

20 *d. Link between coupling strength and convection.*

21 Coupling strength is a net result of complex interactions between numerous process
22 parameterizations in the AGCM. We have discerned different behaviors of land-atmosphere

1 coupling among the 12 GCMs in this study and have broken down the contributions to this
2 coupling from the atmospheric and terrestrial branches of the hydrologic cycle. Can we identify
3 the process parameterizations that are mostly responsible for the differing coupling strengths?

4 We now examine moist convective precipitation with this in mind. Given that moist
5 convection is often instigated by variations in near surface air temperature and humidity, whereas
6 large scale condensation is strongly controlled by variations in the general circulation, we might
7 naturally expect moist convection to be a key component of the pathway linking soil moisture
8 variations and precipitation. Figure 11a shows the global average of $\Omega_P(S) - \Omega_P(W)$ calculated
9 separately for total precipitation, convective precipitation, and large-scale precipitation. (Note
10 that only seven models reported the precipitation components separately.) With the exception of
11 the NSIPP model, the contribution of soil moisture to similarity in the convective component is
12 60-200% greater than its contribution to similarity in the large-scale component. The fact that
13 $\Omega_P(S) - \Omega_P(W)$ tends to be larger for convective precipitation than for large-scale precipitation
14 supports the idea that convective precipitation is more sensitive to land surface moisture
15 variations.

16 In Figure 11b, the $\Omega_P(S) - \Omega_P(W)$ values are weighted by the fractional contributions of
17 the convective precipitation component to total precipitation. This plot shows that convective
18 precipitation bears most of the signal of soil moisture's impact on precipitation, due in large part
19 to the dominance of convective precipitation during boreal summer. Based on the bottom plot,
20 the coupling between surface fluxes and precipitation is indeed via the convective precipitation
21 scheme in the AGCMs.

Not examined separately here are the many aspects of the moist convective parameterization (convective triggers, depth of detrainment, droplet microphysics, evaporation of falling rain, downdrafts) that can affect the evolution of temperature and humidity of the boundary layer and can thus induce intermodel differences in simulated land-atmosphere coupling strength. Additional sensitivity experiments with more comprehensive diagnostics, perhaps in a single column model setting, would be needed to address more fully the role of moist convection in the coupling.

4. Discussion and Summary

Through coordinated numerical experiments with a dozen AGCMs as part of the GLACE project, the impacts of soil moisture conditions on rainfall generation have been examined for the boreal summer season. These impacts are found to be a function of hydroclimatological regime and are heavily affected by the complex physical process parameterizations implemented in the AGCM.

In general, impacts of soil moisture on rainfall are strong only in the transition zones between dry and wet areas. Multi-model analysis shows that the existence of “hot spots” of land-atmosphere coupling in these areas is due to the coexistence there of a high sensitivity of ET to soil moisture and a high temporal variability of the ET signal. In wet climates, where soil moisture is plentiful, ET is controlled not by soil moisture but by atmospheric demand (as determined in part by net radiation). Specifying land moisture states in wet climates thus has little impact on ET and rainfall generation (cases i and ii in Figure 2). In dry climates, ET rates are sensitive to soil moisture, but the typical variations are generally too small to affect rainfall

1 generation (case iii in Figure 2). Only in the transition zone between wet and dry climates,
2 where ET variations are suitably high but are still sensitive to soil moisture, do the land states
3 tend to have strong impacts on precipitation.

4 The impact of soil moisture on rainfall varies widely from model to model. The GFDL,
5 CAM3, and NSIPP models have the strongest land-atmosphere coupling strengths, and
6 GFS/OSU, HadAM3, BMRC, and GEOS have the weakest (Table 1). The breakdown of the
7 coupling mechanism into two segments, the link between soil moisture and evaporation and the
8 link between evaporation and precipitation, helps to identify some of the reasons for these
9 differences. Some models (CAM3, NSIPP) have a high coupling strength because their modeled
10 atmospheres (particularly their convective schemes) are strongly sensitive to evaporation
11 variations, whereas the atmospheres of other models (HadAM3, GEOS) are relatively insensitive
12 to evaporation variations, leading to a weak coupling strength. Most of the intermodel
13 differences in coupling strength, however, can be explained by intermodel differences in the
14 nature of the evaporation signal itself, as characterized by the diagnostic product $(\Omega_E(S)-$
15 $\Omega_E(W)) \cdot \sigma_E(W)$. Figure 6 suggests that in some of the hotspot regions of strong coupling,
16 intermodel variations in the diagnostic product can explain more than 80% of intermodel
17 variations in coupling strength. Figures 8a and 10 summarize the impacts of the various factors
18 on globally-averaged coupling strength for each model.

19 In the companion paper (Koster et al, this issue), we noted that the Ω_P diagnostic does not
20 distinguish between local and remote land surface influences on precipitation. One interpretation
21 of the overall strong performance of the diagnostic product $(\Omega_E(S)-\Omega_E(W)) \cdot \sigma_E(W)$ in

1 reproducing Ω_P is that the coupling between precipitation and soil moisture is indeed largely
2 local. Additional experiments would be needed to demonstrate this more definitively.

3 For the understanding of land-atmosphere coupling strength, we can identify several
4 additional issues that require further attention. First, an objective quantification of large-scale
5 coupling strength from observational data needs to be obtained; its absence is a major obstacle to
6 the evaluation of model performance. Second, land-atmosphere coupling strength should be
7 quantified for other seasons; presumably it will be weaker during seasons that feature less moist
8 convection, though preliminary experiments with the CCSR/NIES model (not shown) suggest
9 otherwise. Third, for a more detailed analysis of coupling strength in a more controlled setting,
10 different configurations of convective precipitation schemes, boundary layer schemes, and ET
11 formulations should be applied within individual models. In particular, the use of implicit
12 coupling of the land surface to the atmosphere (Polcher et al. 1998; Best et al. 2004) rather than
13 the more common explicit or semi-implicit approaches should be investigated, as the former may
14 lead to a “tighter” connection between the land surface and the planetary boundary layer, with
15 consequent impacts on derived coupling strength. Finally, the strength of land-atmosphere
16 coupling should be quantified relative to that of other controls in the Earth’s climate system; for
17 example, comparing the GLACE results above with those from a separate set of ensembles that
18 use different SST boundary conditions for each ensemble member (drawn from observed
19 interannual SST distributions) could establish the relative importance of land and ocean controls
20 on precipitation variability.

21

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3 the weighted similarity diagnostic $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$ across all twelve models.

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6 high σ_E . (see text for details).

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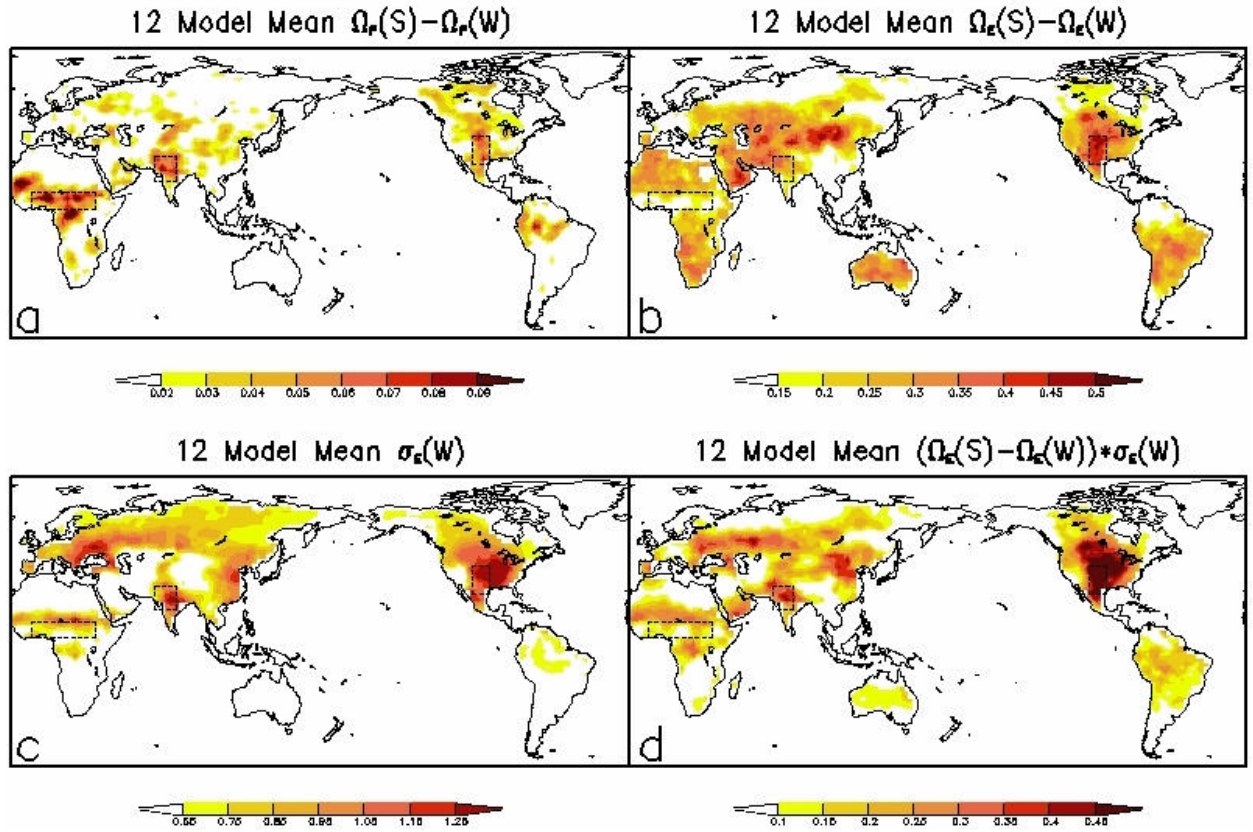
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Model	SW—Precip. Rank		SW—ET Rank		(ET—Precip.) ₁ Rank		(ET—Precip.) ₂ Rank	
GFDL	0.040	1	0.387	1	0.211	7	0.104	4
NSIPP	0.034	2	0.140	5	0.511	2	0.241	2
CAM3	0.032	3	0.129	7	0.715	1	0.248	1
CCCma	0.024	4	0.249	2	0.450	4	0.095	7
CSIRO	0.014	5	0.151	4	0.042	11	0.097	6
UCLA	0.011	6	0.114	8	0.267	6	0.099	5
CCSR	0.009	7	0.104	9	0.453	3	0.090	8
COLA	0.009	8	0.081	11	0.370	5	0.106	3
GEOS	0.006	9	0.209	3	0.162	9	0.030	10
BMRC	0.005	10	0.102	10	0.182	8	0.047	9
HadAM3	0.002	11	0.129	6	-0.016	12	0.012	11
GFS	-0.004	12	0.024	12	0.082	10	-0.017	12

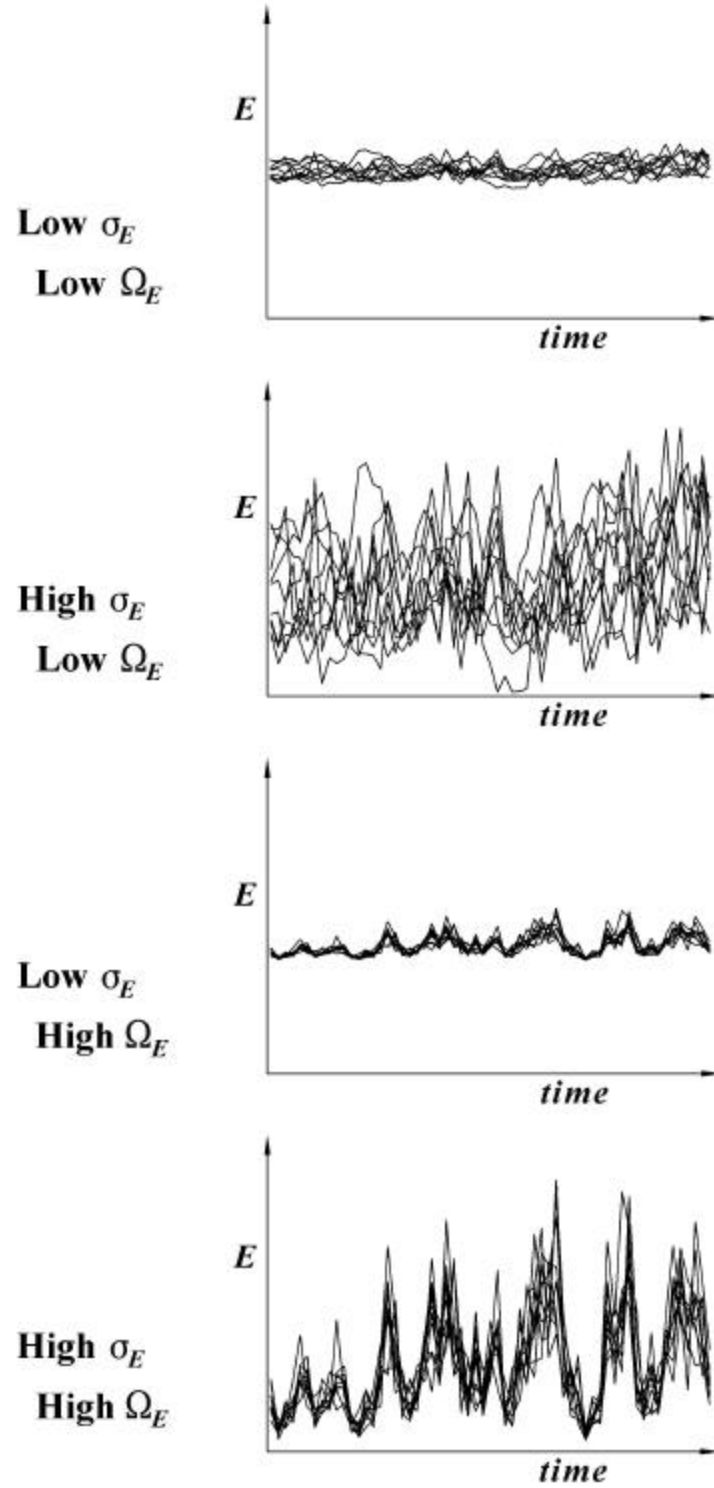
2 Table 1. Globally-averaged (over non-ice land points) land-atmosphere coupling strength for all
3 twelve models and in each segment of the path from soil wetness to precipitation, namely soil
4 wetness - ET and ET – Precipitation. (See text for details.)

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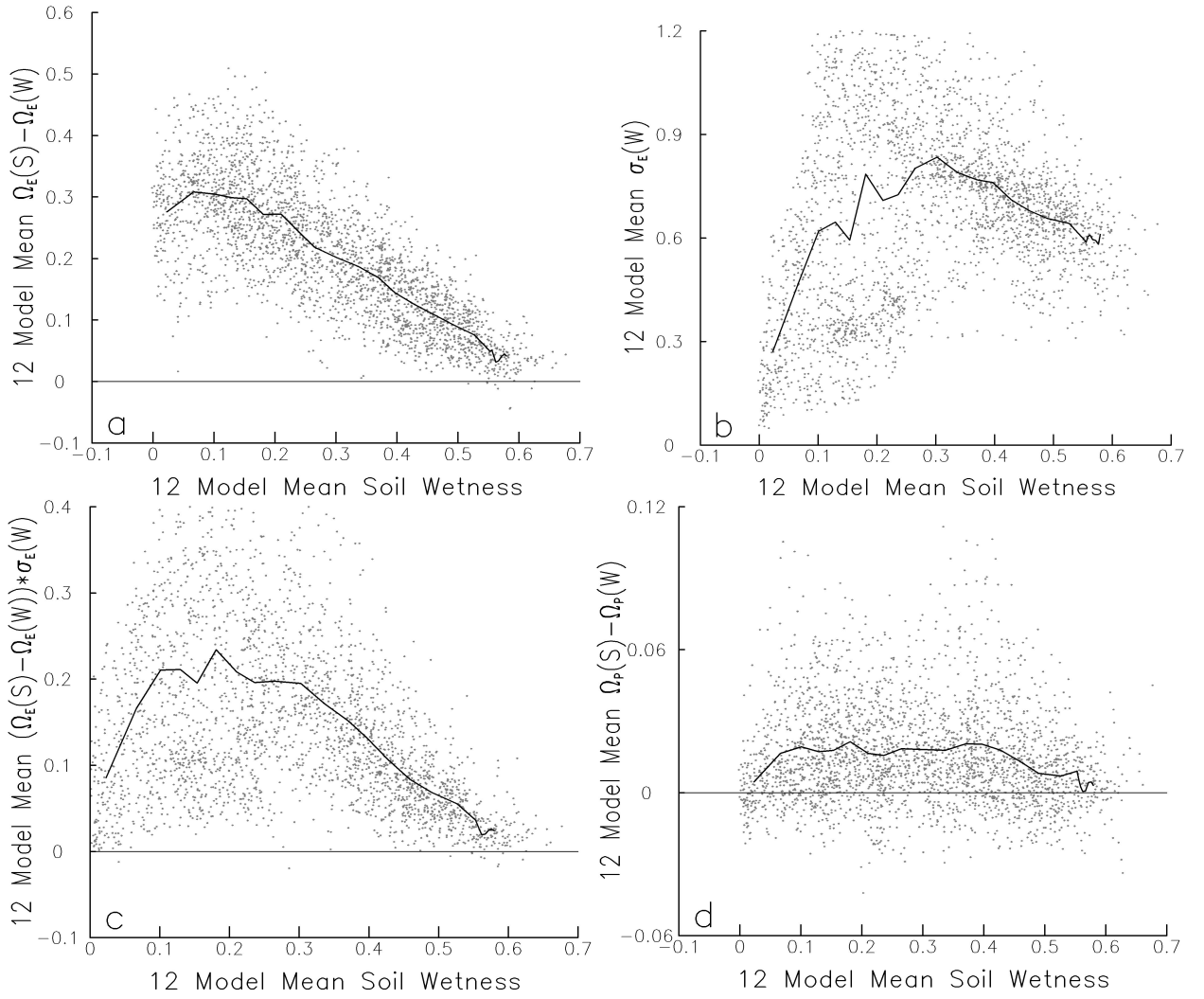
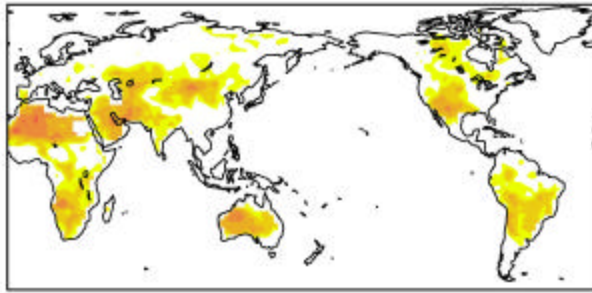
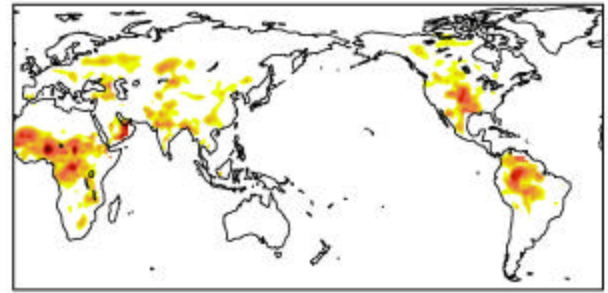


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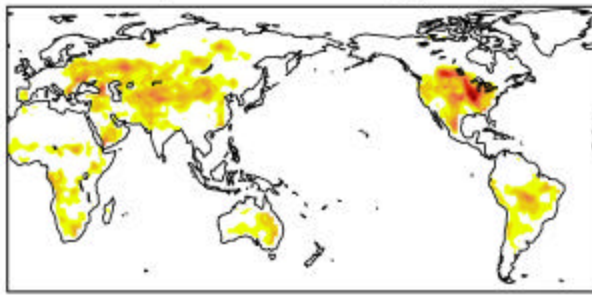
StdDev of $\Omega_E(S) - \Omega_E(W)$ among 12 Models



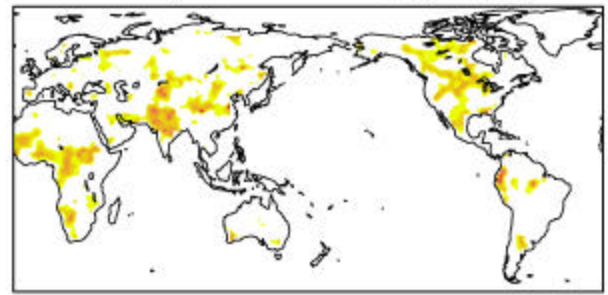
StdDev of $\Omega_P(S) - \Omega_P(W)$ among 12 Models



Mean / StdDev for $\Omega_E(S) - \Omega_E(W)$



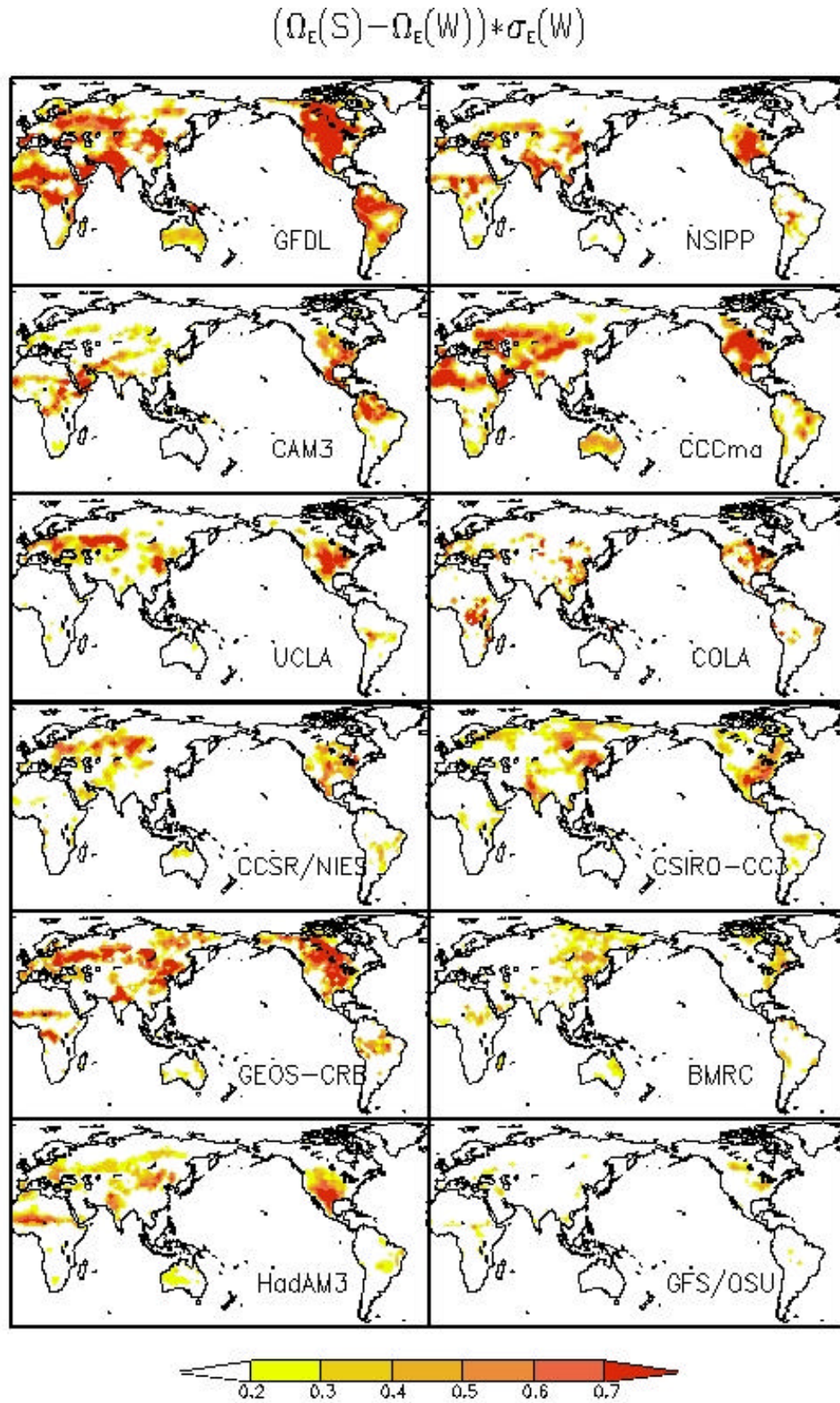
Mean / StdDev for $\Omega_P(S) - \Omega_P(W)$



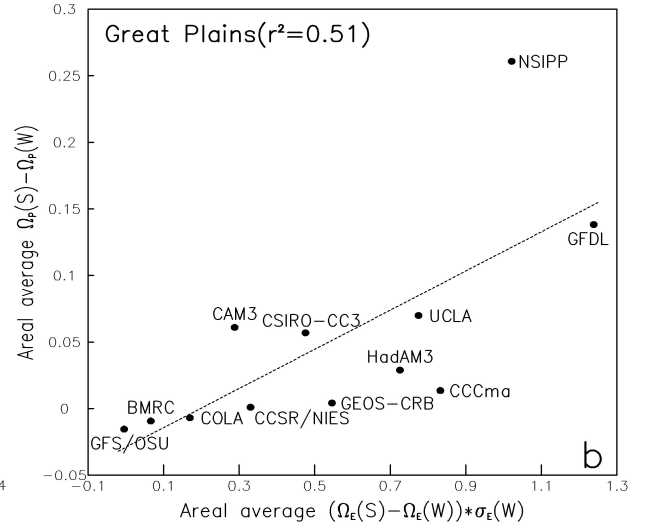
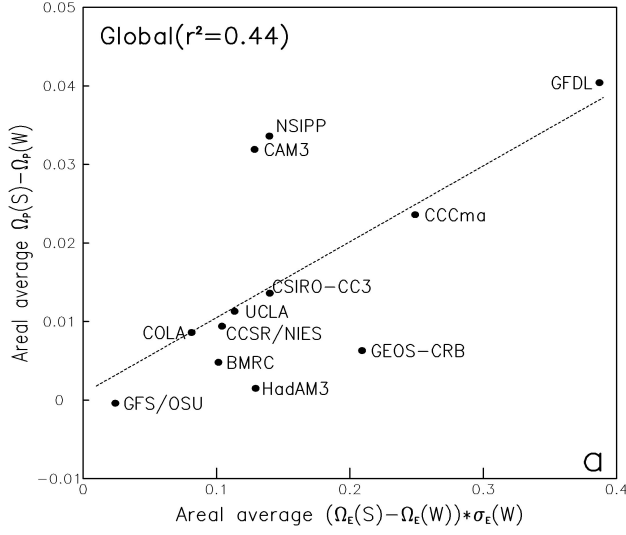
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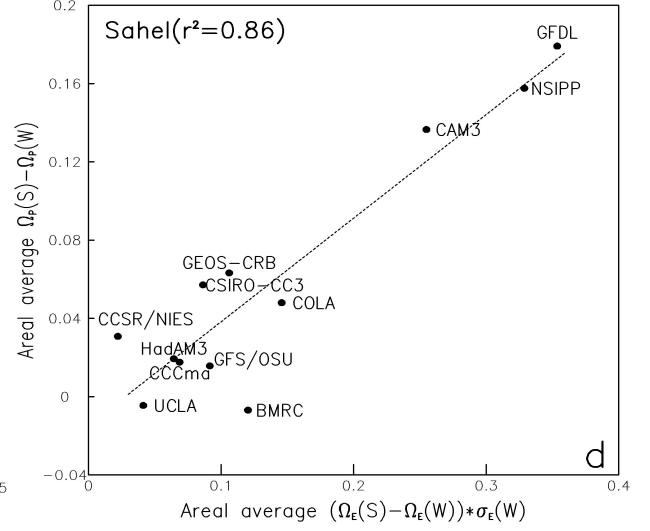
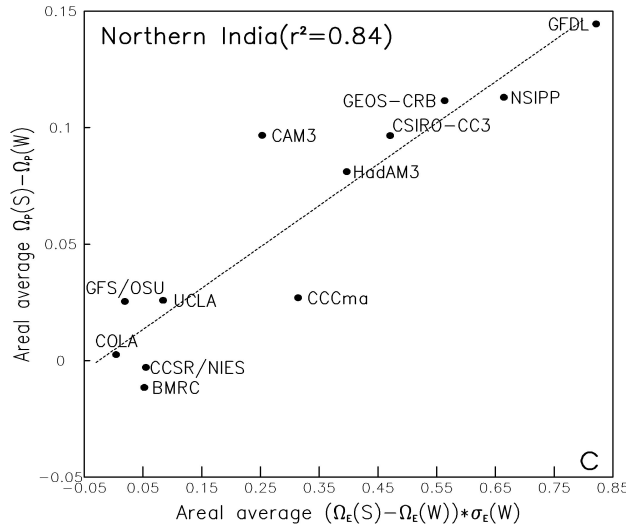
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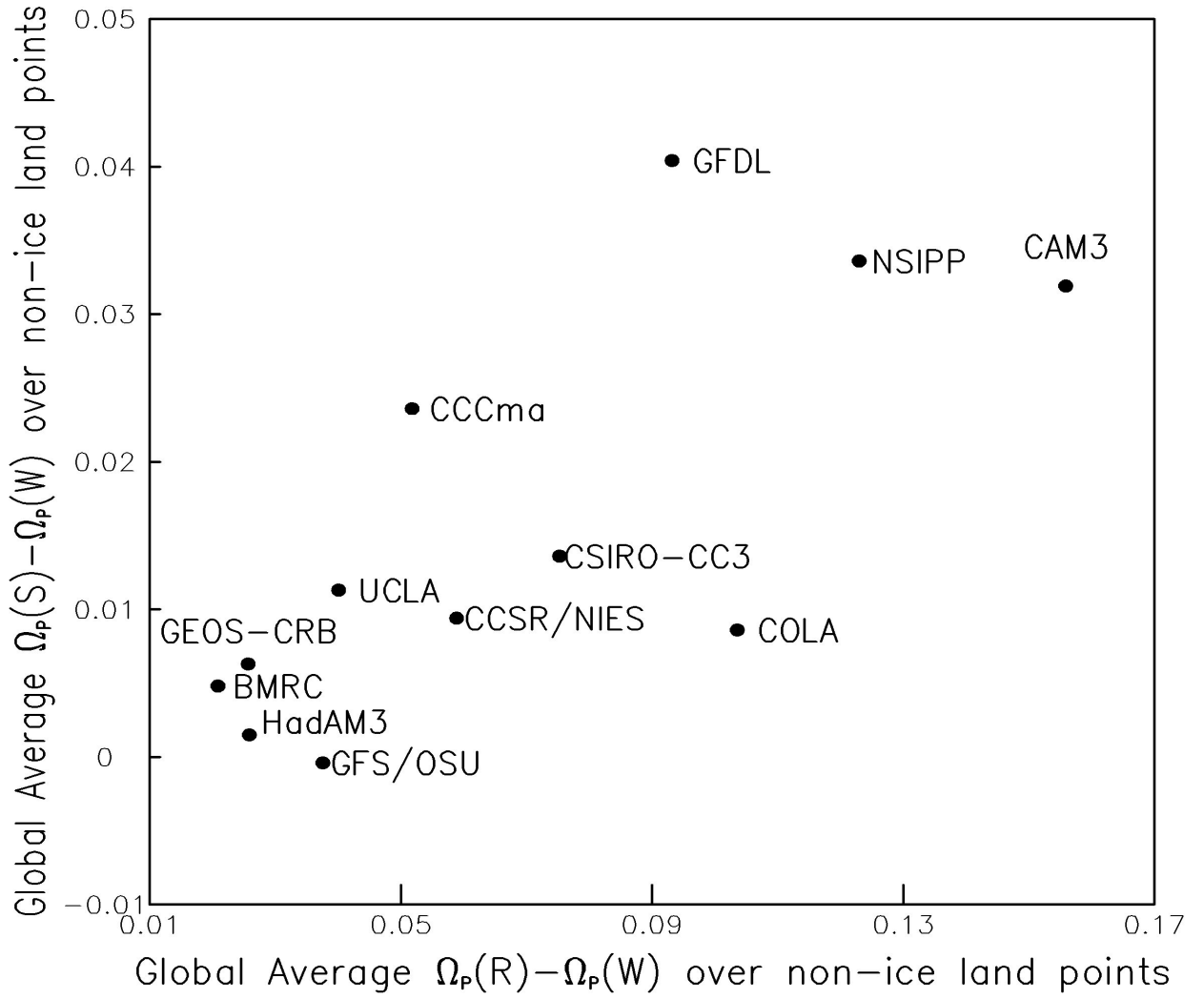


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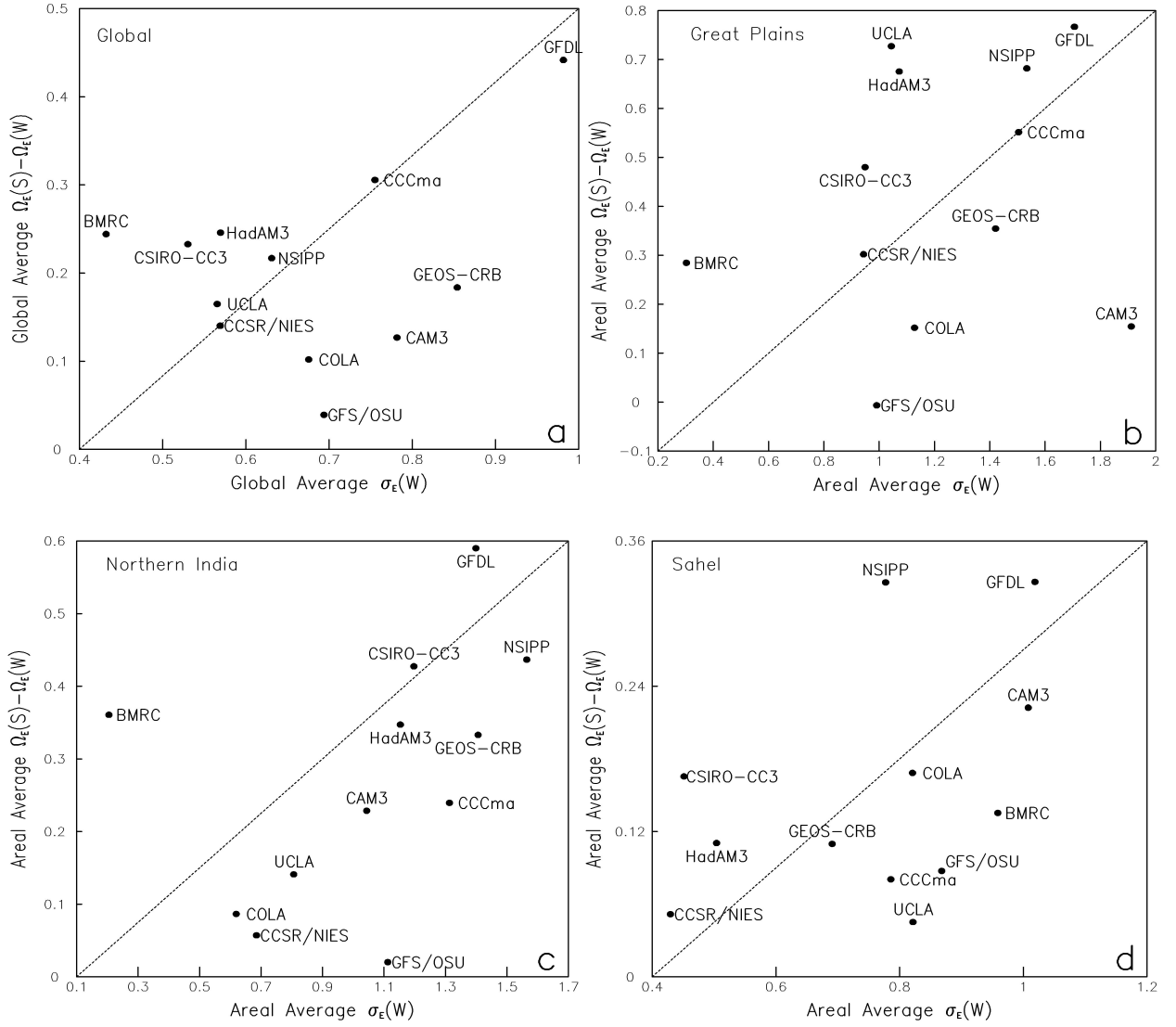
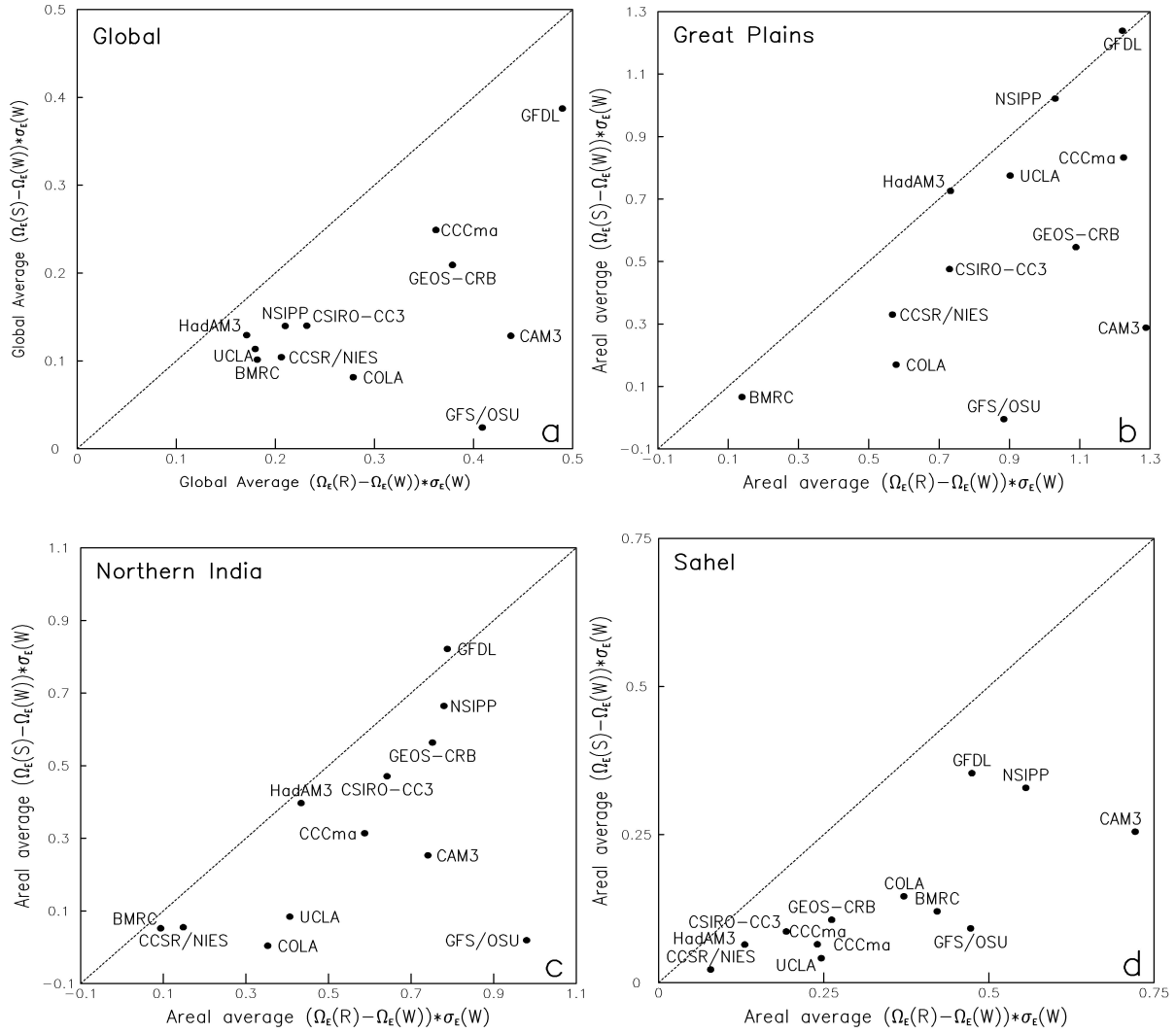


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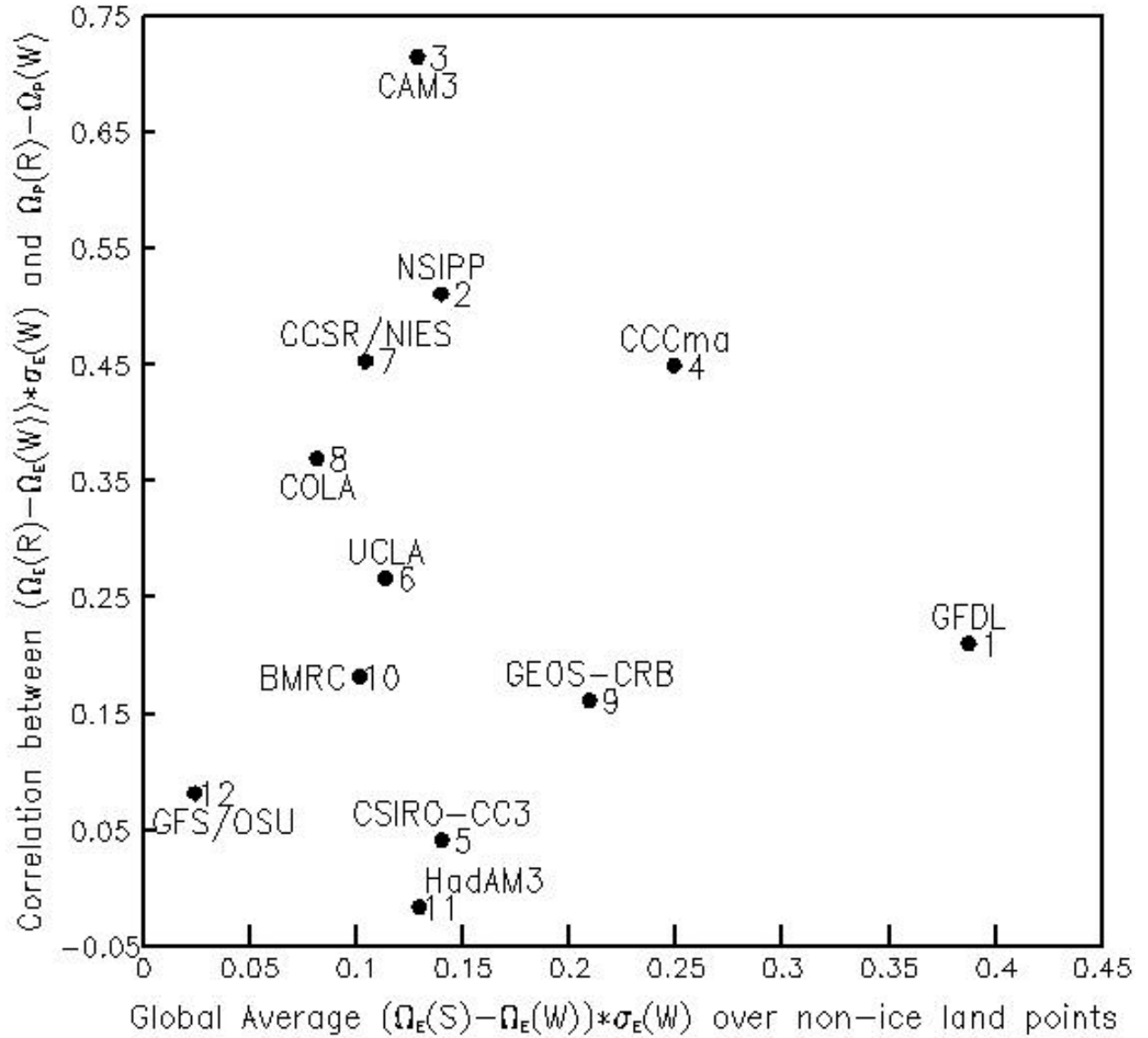


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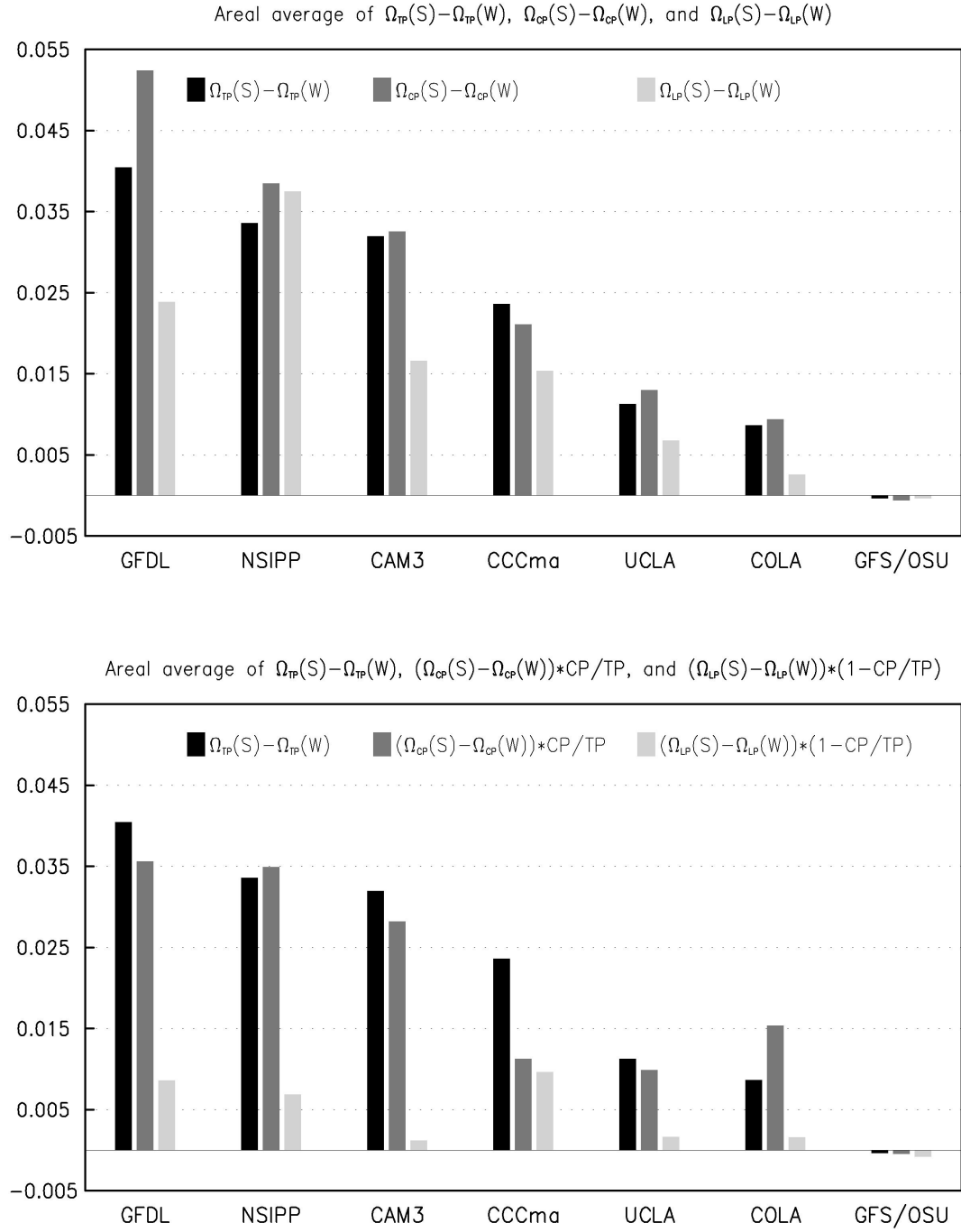
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